IN3020&4020 – Database Systems (2025)
Part 1: Query Processing
Lectures 11, 12, 13: Query Compilation and Optimisation

24, 25 February, 2 March

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Big Picture (reminder)

Syllabus of the course:

- (Extended) Intro and SQL recap ✓

Part 1. Query processing in relational databases

Part 2. Transaction management in relational databases

Part 3. NoSQL DBMS

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SQL query processing relies on two key ingredients:
Relational Algebra (✓) and Indexes (✓)

We have studied these ingredients (almost in isolation)
and now put all things together

SQL (DQL) query processor in action

```
SELECT DISTINCT title FROM StarsIn WHERE starName IN
  (SELECT name FROM MovieStar WHERE birthDate LIKE '%1960');
```

$\downarrow$ parsing

(parse tree)

$\downarrow$ compilation

$$\pi_{title}(\sigma_{starName=name}(\mathbf{StarIn} \times \pi_{name}(\sigma_{birthDate\ LIKE\ '\%1960'}(\mathbf{MovieStar}))))$$

$\downarrow$ optimisation

$$\pi_{title}(\mathbf{StarIn} \bowtie_{starName=name} \pi_{name}(\sigma_{birthDate\ LIKE\ '\%1960'}(\mathbf{MovieStar})))$$

$\downarrow$ evaluation over tables

(Result)

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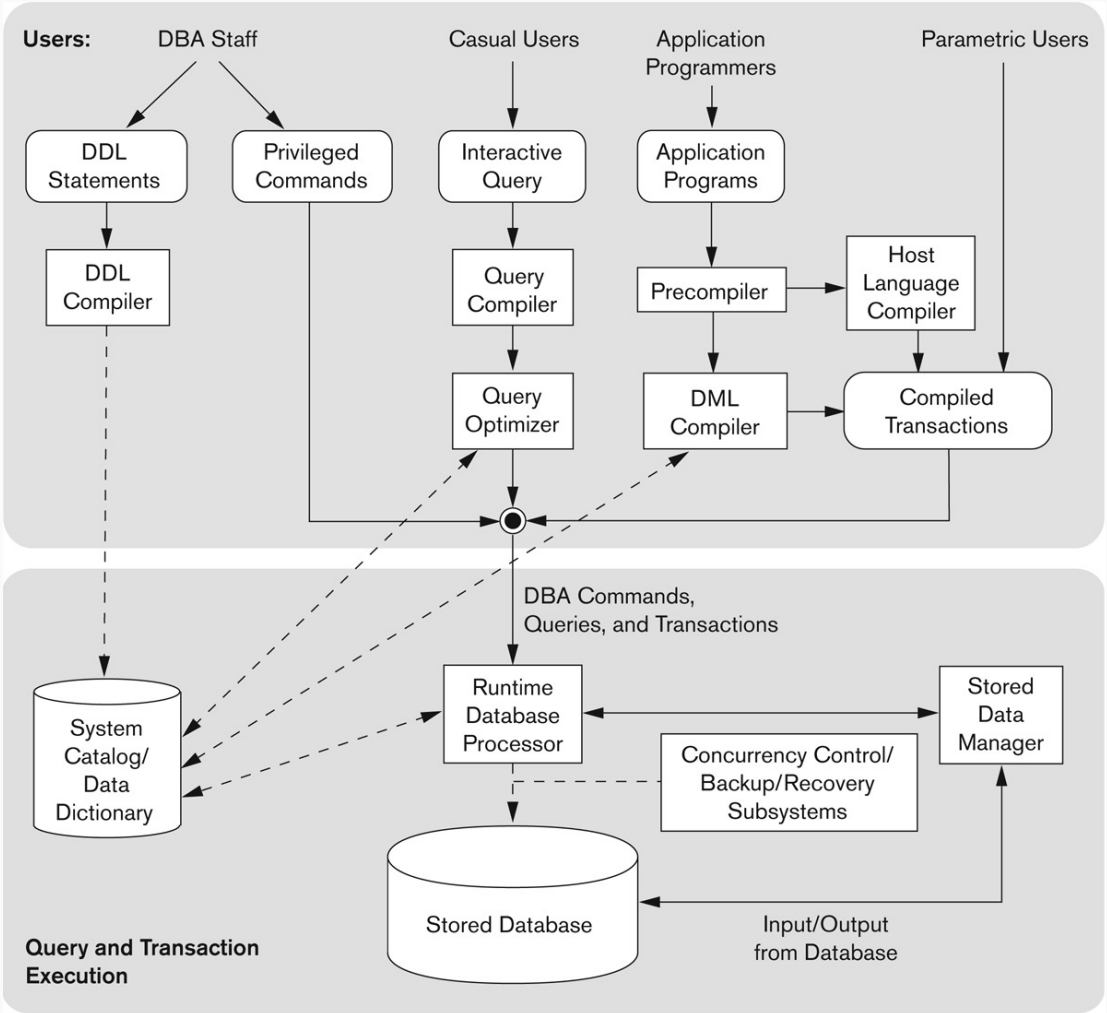
$\downarrow$ optimisation

$$\pi_{title}(\mathbf{StarIn} \bowtie_{starName=name} \pi_{name}(\sigma_{birthDate\ LIKE\ '\%1960'}(\mathbf{MovieStar})))$$

$\downarrow$ evaluation over tables (next time)

(Result)

The place of parsing and optimisation



Materials to read about query compilation and optimisation

1. *Fundamentals of Database Systems* by R. Elmasri and S.B. Navathe (7th edition): Chapter 18 (beginning) and 19
   (my lectures have different accents)

2. *Database Systems: the Complete Book* by H. Garcia-Molina, J. Ullman & J. Widom (2nd edition): Section 16
   (closer to my presentation)

3. etc.

Lecture Plan

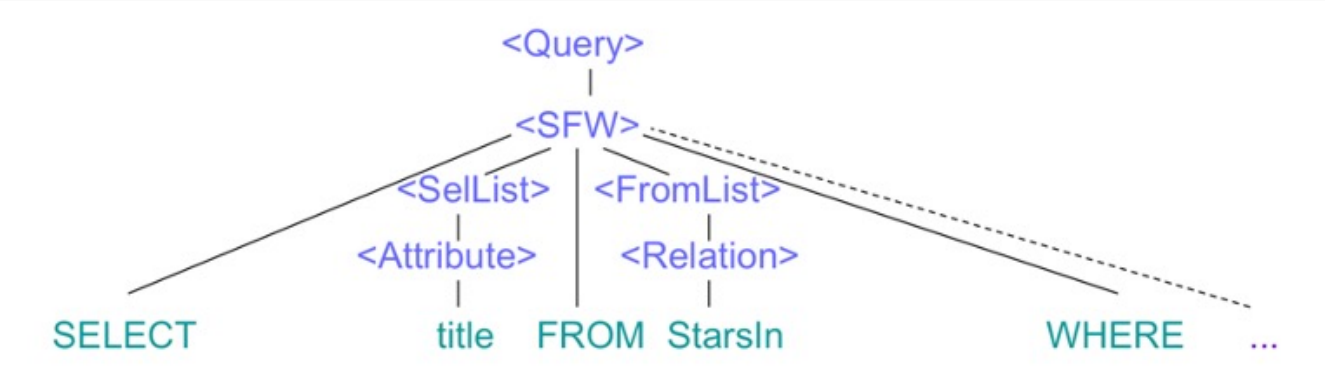
1. Parsing
2. Compilation
3. Optimisation: Overview
4. Optimisation: Cost Function
5. Optimisation: Heuristics

1. Parsing

Parsing: overview

Parsing transforms an SQL (SELECT) query to a parse tree—

that is, from `SELECT title FROM StarsIn WHERE ...` to



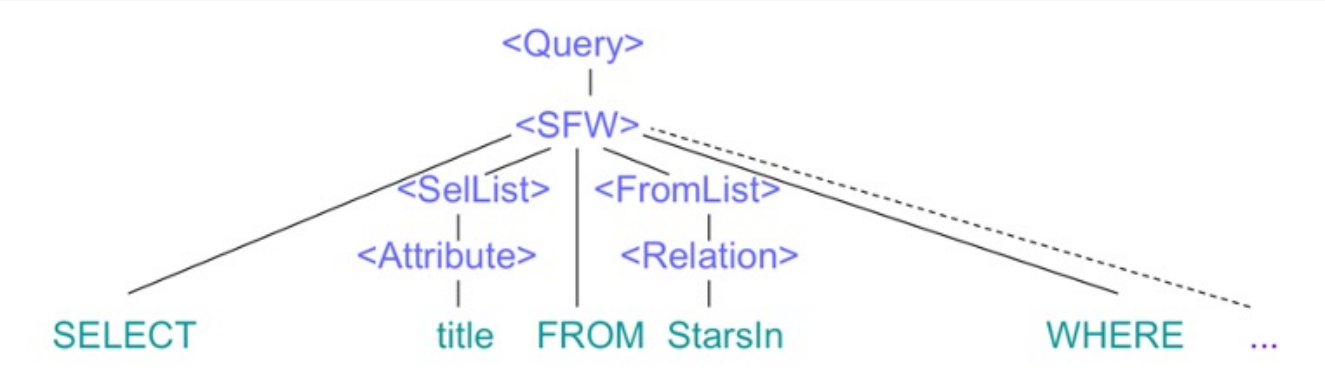
Parse tree:

- inner nodes are syntactic categories for parts of the query
- leaves are primitive atoms representing keywords, names, constants, parentheses, operators, etc.

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Parse tree:

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Parsing is done by standard techniques using a (context-free) grammar for SQL (see details in a Compiler Book)

Excerpt of SQL (DQL) grammar in BNF

```
<Query> ::= <SFW> | "(" <Query> ")" | <Query> "UNION" <Query> | ...

<SFW> ::= "SELECT" (<SelList>|"*") "FROM" <FromList> ["WHERE" <Condition>]
            ["GROUP BY" ... ["HAVING" ... ]]  ["ORDER BY" ... ]

<SelList> ::= <Attribute> | <Attribute> "," <SelList> | ...

<FromList> ::= <Relation> | <Relation> "," <FromList> | ...

<Condition> ::= <Condition> "AND" <Condition> | "NOT" <Cond> |
              <Attribute> "IN" <Query> | <Attribute> "=" <Attribute> | ...

  ...

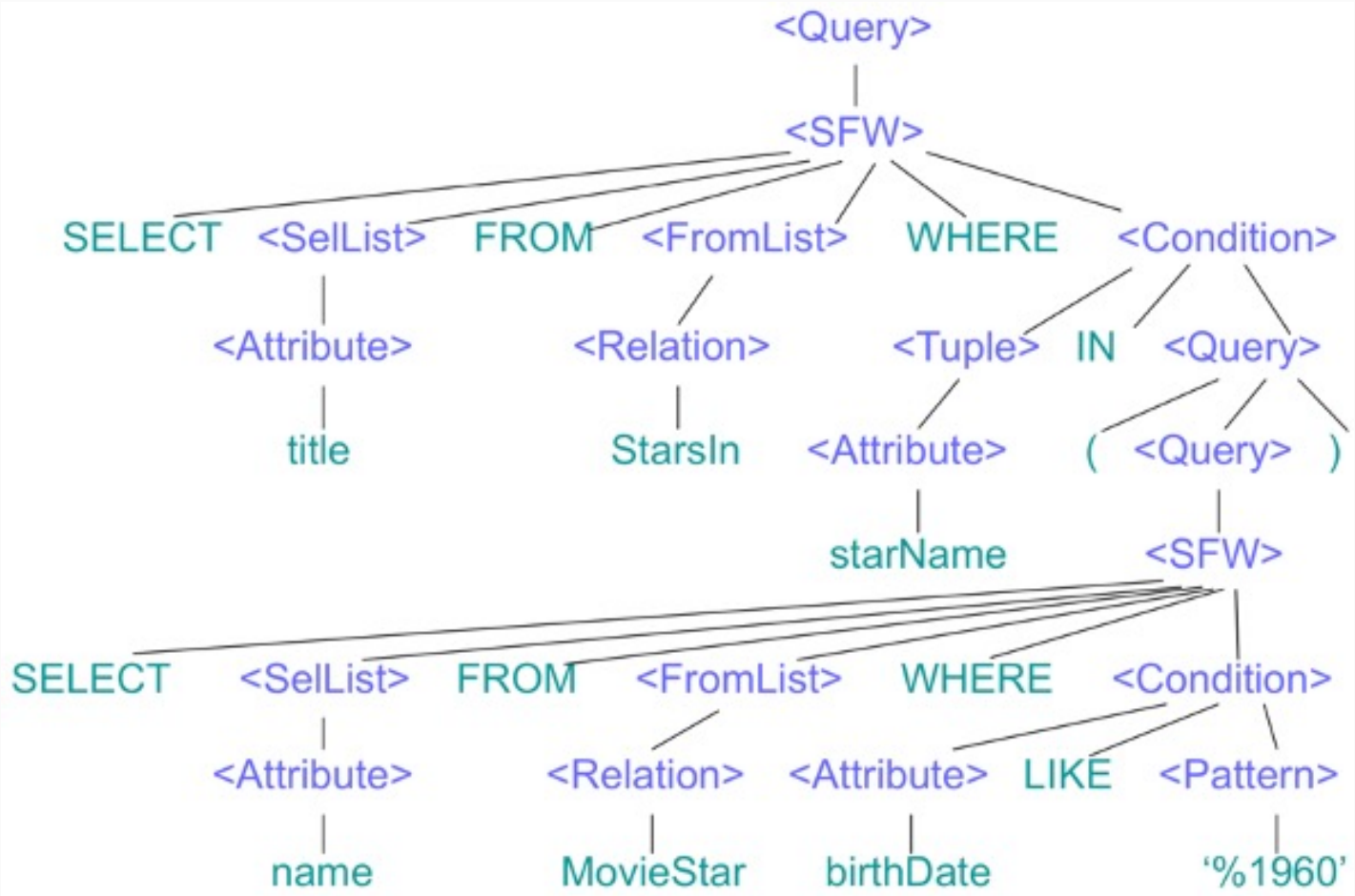
<Attribute>, <Relation> ::= ...     (parse to strings of symbols)

  ...
```

Parsing: Example

```
SELECT title FROM StarsIn WHERE starName IN
  ( SELECT name FROM MovieStar WHERE birthDate LIKE '%1960' );
```

parses to



Resolving names and type checking

Besides building the tree, several checks is done using the System Catalog:

- resolving names: checking that all the tables and attributes exist (and, if successful, linking them)
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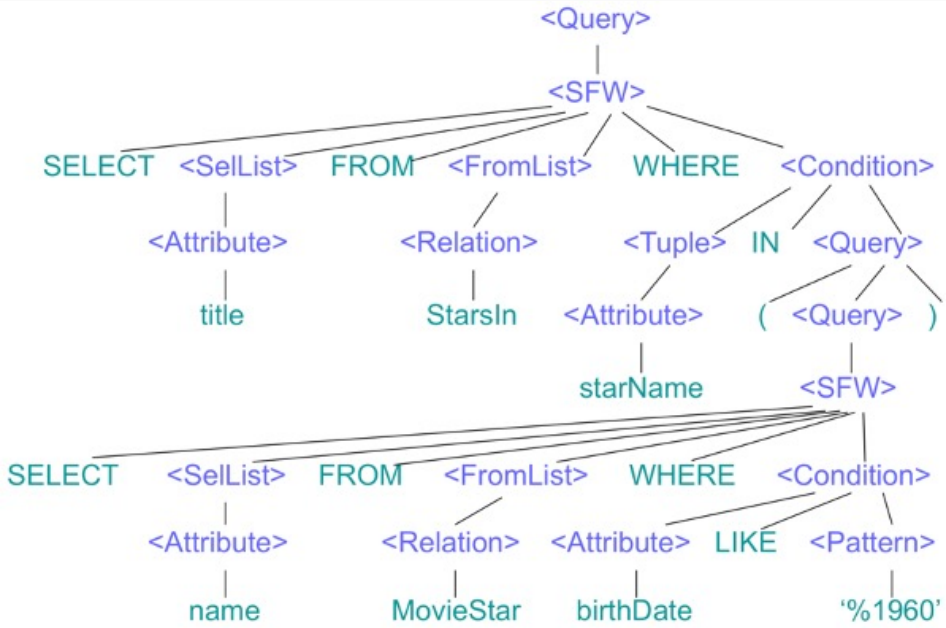
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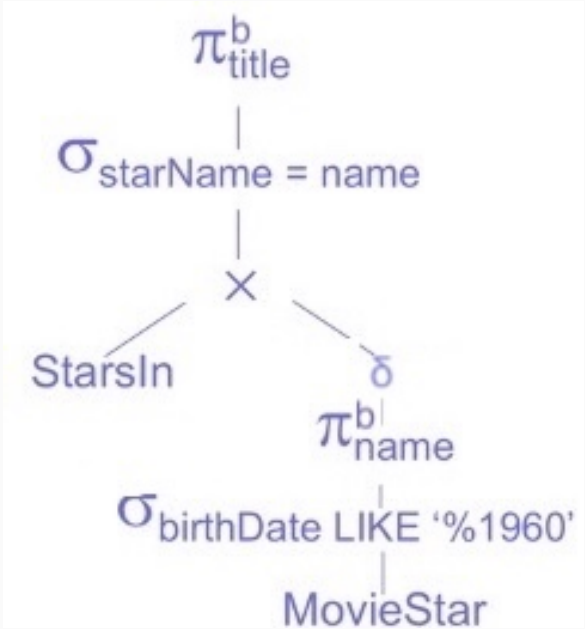
Both building the tree and the checks can fail

2. Compilation

Query compilation: Idea

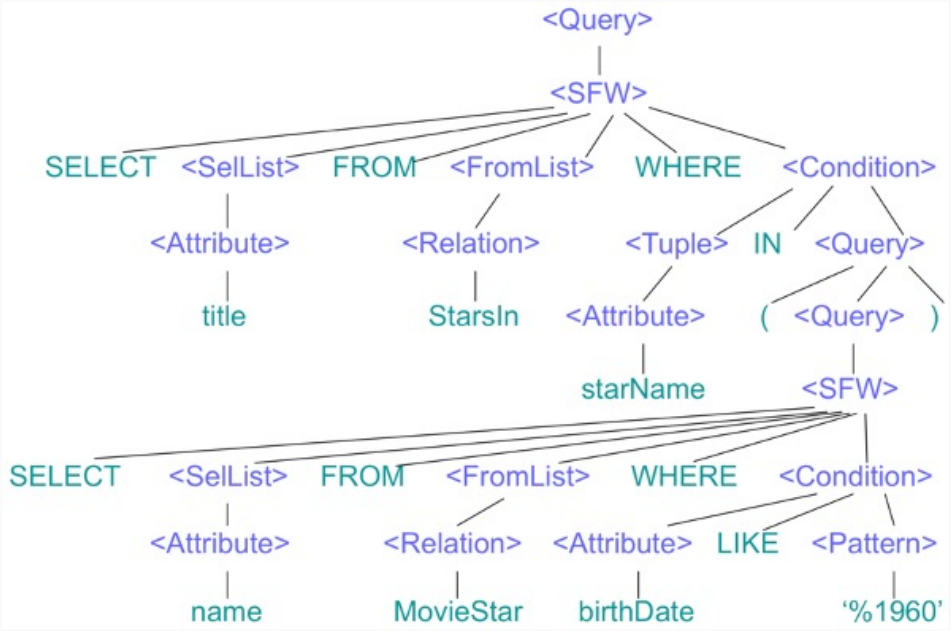
Converts (i.e., 'compiles') the parse tree to an RA expression, called initial (logical) query plan:

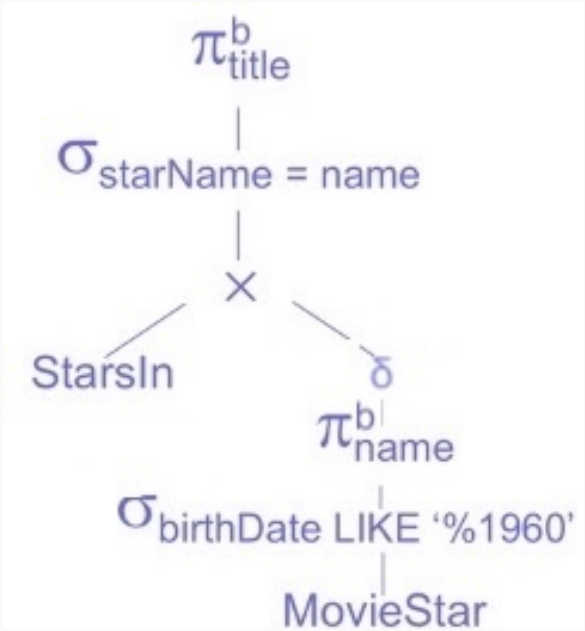




Query compilation: Idea

Converts (i.e., 'compiles') the parse tree to an RA expression, called initial (logical) query plan:





Note 1: I use tree-like representation for the RA expression (natural and intuitive)

Note 2: I use the relation names instead of full relations (for brevity)

Query compilation: Subquery-free case

Compilation without subqueries is direct

For example, the parse tree for

`SELECT` Atts `FROM` Table1, ..., TableM `WHERE` C

with Table1, ..., TableM without common attributes compiles as

- replace Table1, ..., TableM with
  (...(Table1 $\times$ Table2) $\times$ ...) $\times$ TableM in the tree
- apply selection $\sigma_C(\ldots)$ to the product
- apply (bag) projection $\pi^b_{Atts}(\ldots)$ to the selection

If Table1, ..., TableM have common attributes, we need renaming

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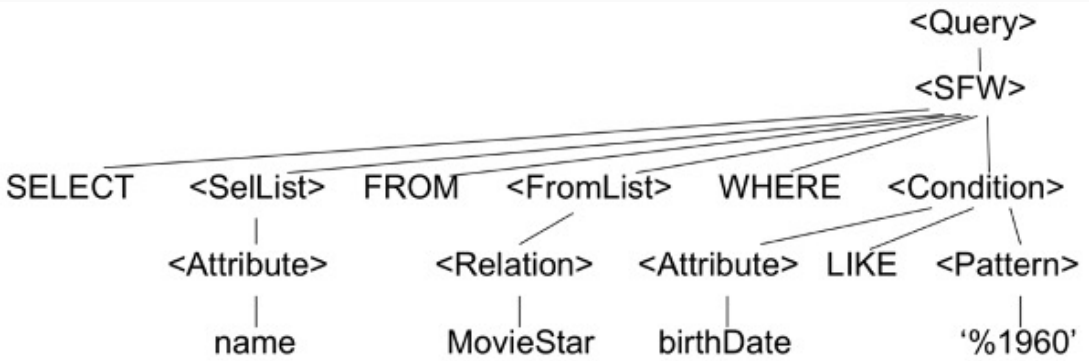
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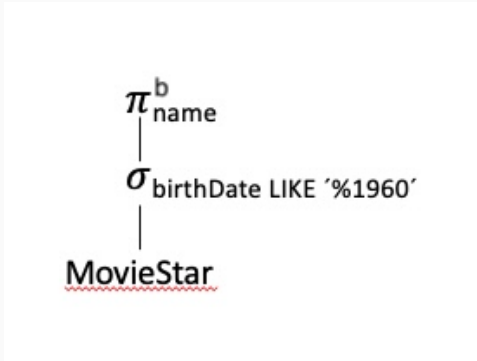
Note: `INNER JOIN ... ON ...`, `OUTER JOIN ... ON ...` make two copies of join attributes; need care when compiling to $\bowtie_C$, $\rtimes$

Query compilation: Subquery-free example

```
SELECT name FROM MovieStar WHERE birthDate LIKE '%1960'
```







Compiling queries with subqueires

Recall: FROM clause may mention sub-SELECT

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Recall: conditions in WHERE clause can also have subqueries:

```
SELECT ... WHERE ... EXISTS(SELECT ... )  ... ;

SELECT ... WHERE ... (Att1, ..., AttN) op SOME(SELECT ... )  ... ;

SELECT ... WHERE ... (Att1, ..., AttN) op ALL(SELECT ... )  ... ;
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here, op is one of $=$, $>=$, $>$, ...

`SOME(...)` has synonym `ANY(...)`

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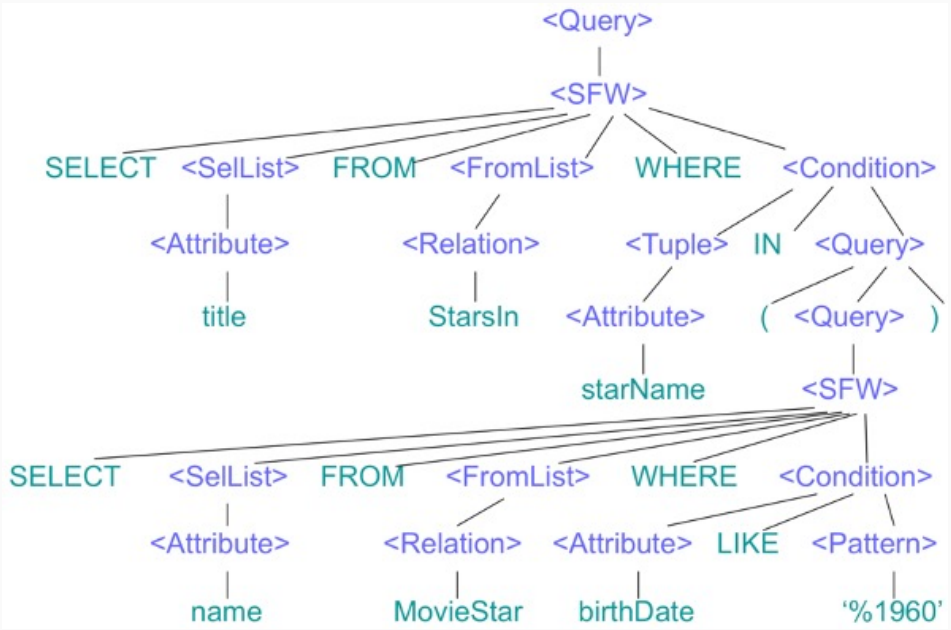
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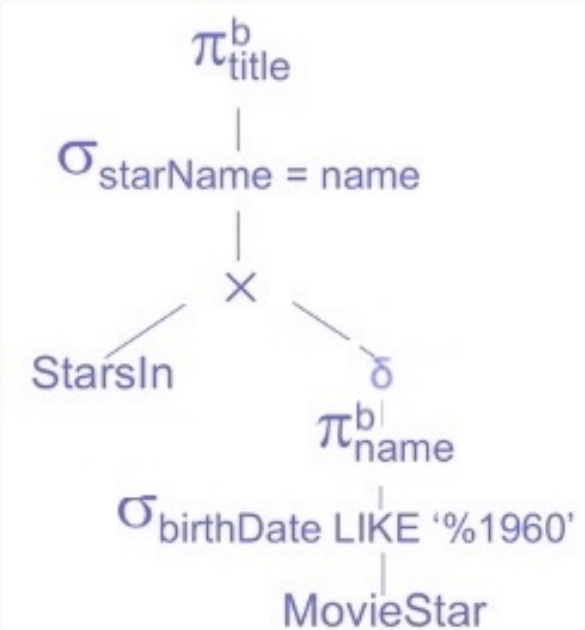
Compiling subqueries is more challenging,

especially with correlated attributes (but always possible)

Non-correlated IN-subqueries

```
SELECT title FROM StarsIn WHERE starName IN
  ( SELECT name FROM MovieStar WHERE birthDate LIKE '%1960' );
```

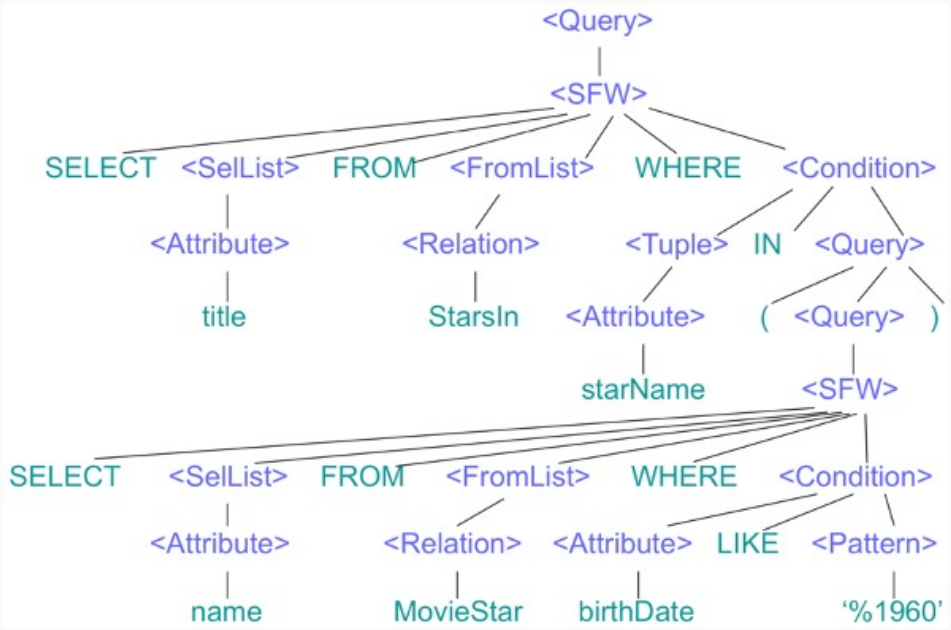


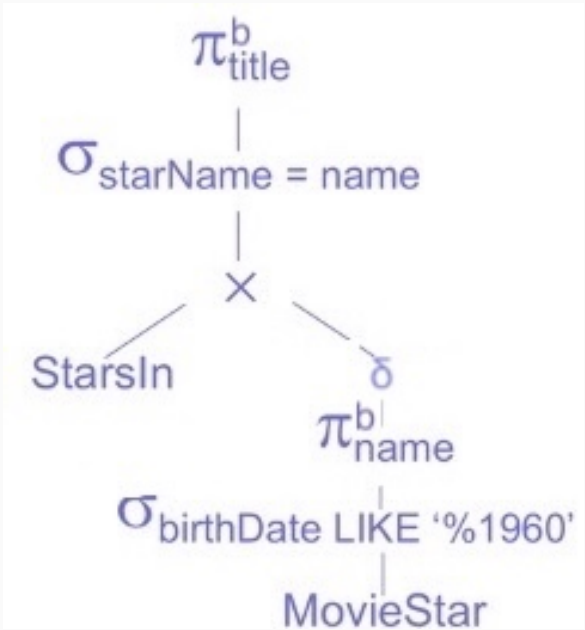


Alternatively:

Non-correlated IN-subqueries

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SELECT title FROM StarsIn WHERE starName IN
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Alternatively:

$$\pi^b_{title}(StarsIn \ltimes (\pi_{name \to starName}(\sigma_{birthDate LIKE '\%1960'}(MovieStar))))$$

Other non-correlated subqueries

Subqueries with NOT IN are symmetric:

```
SELECT title FROM StarsIn WHERE starName NOT IN
  (SELECT name FROM MovieStar WHERE birthDate LIKE '%1960');
```

$$\rightsquigarrow$$

$$\pi^{b}_{title}(StarsIn \triangleright (\pi_{name \rightarrow starName}(\sigma_{birthDateLIKE'\%1960'}(MovieStar))))$$

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If a condition with a subquery is a sub-condition of a complex Boolean expression, it can be isolated:

```
SELECT title FROM StarsIn WHERE (starName NOT IN
 (SELECT name FROM MovieStar WHERE birthDate LIKE '%1960')) AND Cond;
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Other (non-correlated) sub-queries are similar (incl. subqueries in FROM)

Correlated subqueires by copying

For correlated subqueries, we may create a copy of the outer table in the subquery:

```
SELECT Person.name FROM Person
    WHERE EXISTS(SELECT * FROM Address
            WHERE Person.name = Address.pname);
```

$$\rightsquigarrow$$

$$\pi^{b}_{name}(Person \ltimes (\sigma_{name=pname}(Person \times Address))$$

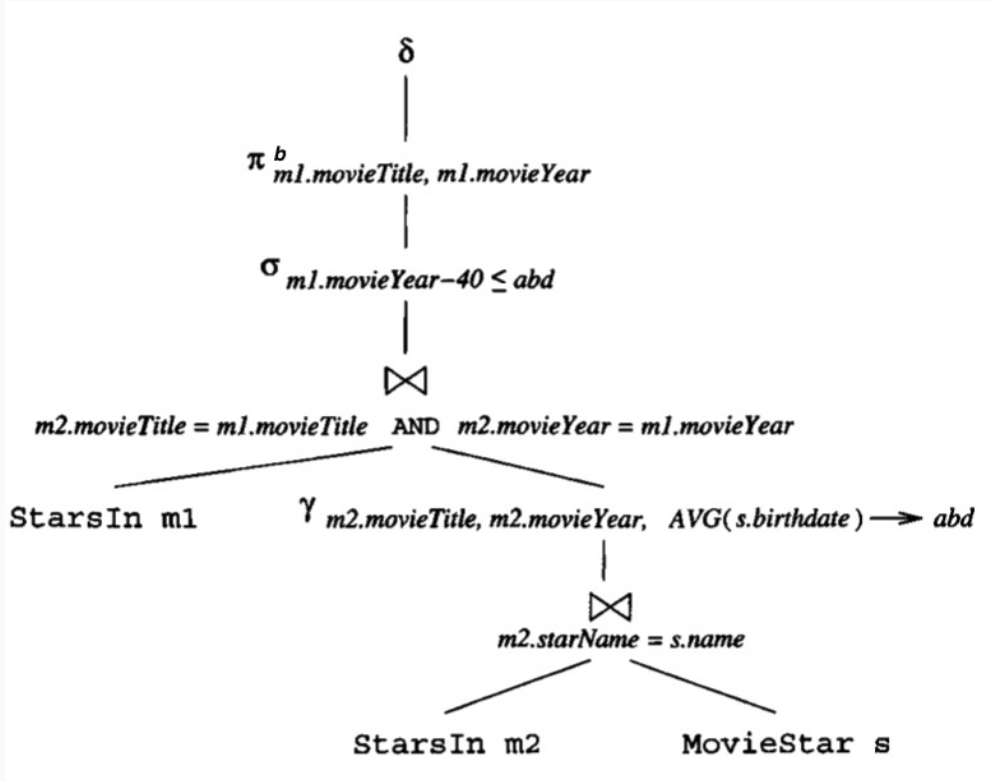
(assuming no common attributes of *Person* and *Address*)

Correlated subqueires by postponing selection

Alternatively, we may postpone the selection

Example: Movies with average age of starring actors at most 40

```
SELECT DISTINCT m1.movieTitle, m1.movieYear
FROM StarsIn m1
WHERE m1.movieYear - 40 <= ANY (
    SELECT AVG(birthdate)
    FROM StarsIn m2, MovieStar s
    WHERE m2.starName = s.name AND
        m1.movieTitle = m2.movieTitle AND
        m1.movieYear = m2.movieYear
);
```



3. Optimisation: Overview

Optimisation: Idealistic goal

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There are few serious (in fact, usually crucial) obstacles

- search space for Expr' is huge (actually, infinite)
- in general, the only way to guarantee that some Expr' can be evaluated quicker than some other Expr is to evaluate both and measure time
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- search space for Expr' is huge (actually, infinite)
- in general, the only way to guarantee that some Expr' can be evaluated quicker than some other Expr is to evaluate both and measure time
- by the way, without the last condition, Expr' is obvious:
  expression constructing the result of Expr (ignoring relations)

Optimisation: Pragmatic approach

Given a (logical) query plan (RA expression) Expr, DBMSs pragmatically find another query plan Expr' such that

- Expr and Expr' are equivalent (i.e., same answer for all tables)
- Expr' is estimated to be quicker than other candidates (for the given tables)
- finding candidate Expr' and estimation is quick

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This approach is based on two components:

1. good cost function f for query plans that is quick to compute and reflects evaluation time (i.e., f(Expr') $<$ f(Expr) in most cases means that Expr' is quicker to evaluate than Expr)
2. good heuristic (usually based on RA algebraic laws) that allows to quickly construct (one or several) candidate Expr' with (much) better cost

Optimisation: Example

```
SELECT B, C, Y FROM R, S WHERE W=X AND A=3 AND Z='a'
```

Relation R

A	B	C	...	W
1	z	1	...	4
2	c	6	...	2
3	r	8	...	7
4	n	9	...	4
2	j	0	...	3
3	t	5	...	9
7	e	3	...	3
8	f	5	...	8
1	h	7	...	5

Relation S

X	Y	Z
1	a	a
2	f	c
3	t	b
4	b	b
7	k	a
6	e	a
7	g	c
8	i	b
9	e	c

Candidate 1: Initial query plan

```
SELECT B, C, Y FROM R, S WHERE W=X AND A=3 AND Z='a'
```

compiles to initial plan

$\pi^b_{B,C,Y}(\sigma_{W=X\ \&\ A=3\ \&\ Z='a'}(R \times S))$

Relation R

A	B	C	...	W
1	z	1	...	4
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Relation S

X	Y	Z
1	a	a
2	f	c
3	t	b
4	b	b
7	k	a
6	e	a
7	g	c
8	i	b
9	e	c

$\overset{\times}{\rightsquigarrow}$

A	B	C	...	W	X	Y	Z
1	z	1	...	4	1	a	a
...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	...
2	c	6	...	2	1	a	a
...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	...
3	r	8	...	7	1	a	a
...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	...
3	r	8	...	7	7	k	a
4	n	9	...	4	1	a	a
...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	v
2	j	0	...	3	1	a	a
...	...	...	...	...	2	c	c
...	...	...	...	...	...	...	...
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...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	...
7	e	3	...	3	1	a	a
...	...	...	...	...	2	f	c
							v

$\overset{\sigma,\pi^b}{\rightsquigarrow}$

B	C	Y
r	8	k

Candidate 1: Initial query plan

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SELECT B, C, Y FROM R, S WHERE W=X AND A=3 AND Z='a'
```

compiles to initial plan

$\pi^b_{B,C,Y}(\sigma_{W=X\ \&\ A=3\ \&\ Z=\text{'a'}}(R \times S))$

Relation R

A	B	C	...	W
1	z	1	...	4
2	c	6	...	2
3	r	8	...	7
4	n	9	...	4
2	j	0	...	3
3	t	5	...	9
7	e	3	...	3
8	f	5	...	8
1	h	7	...	5

Relation S

X	Y	Z
1	a	a
2	f	c
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$\overset{\times}{\rightsquigarrow}$

A	B	C	...	W	X	Y	Z
1	z	1	...	4	1	a	a
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...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	...
3	r	8	...	7	1	a	a
...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	...
3	r	8	...	7	7	k	a
4	n	9	...	4	1	a	a
...	...	...	...	...	2	f	c
...	...	...	...	...	...	...	v
2	j	0	...	3	1	a	a
...	...	...	...	...	2	c	c
...	...	...	...	...	...	...	...
3	t	5	...	9	1	a	a
...	...	...	...	...	2	f	c
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...	...	...	...	...	2	f	c
							v

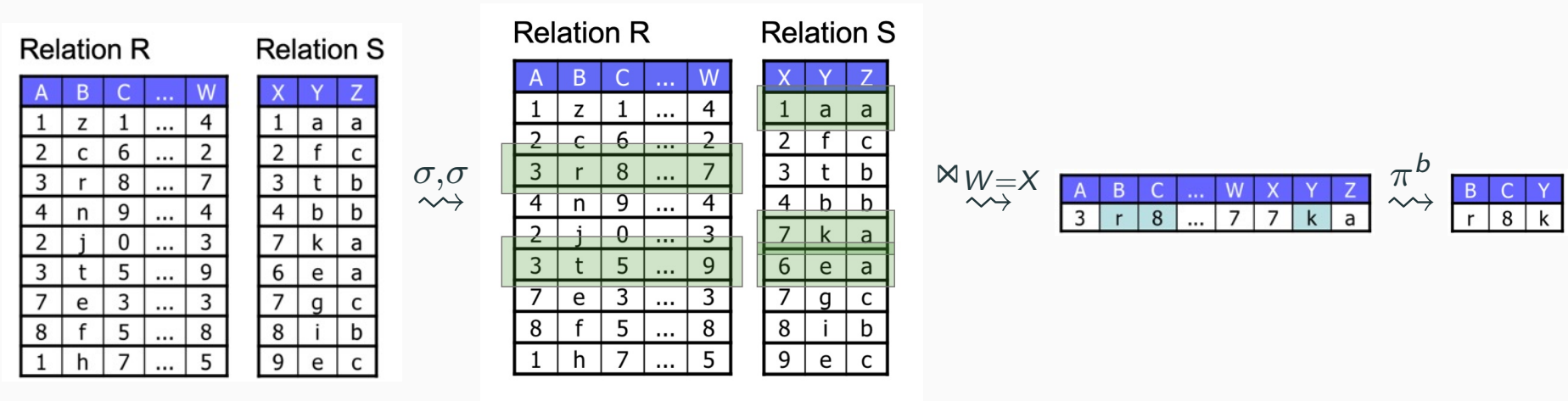
$\overset{\sigma,\pi^b}{\rightsquigarrow}$

B	C	Y
r	8	k

Intuitively, cannot be the most efficient

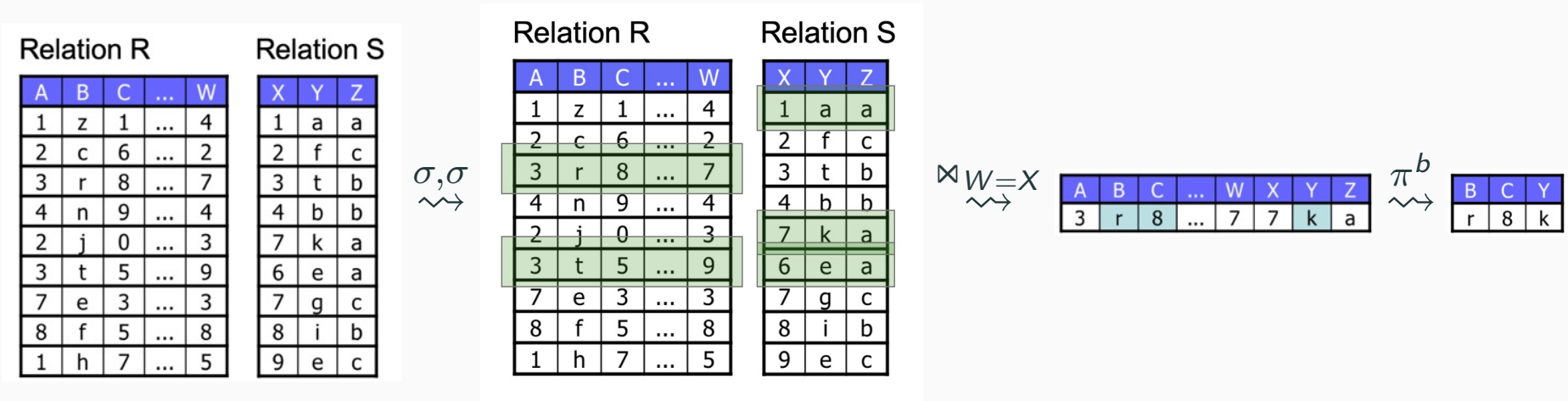
Candidate 2: Pushing selection down

Initial plan $\pi^{b}_{B,C,Y}\ (\sigma_{W=X\ \&\ A=3\ \&\ Z='a'}(R \times S))$
transforms, by pushing selection and theta-join definition laws, to
another plan $\pi^{b}_{B,C,Y}\ (\sigma_{A=3}(R)\ \bowtie_{W=X}\ \sigma_{Z='a'}(S))$



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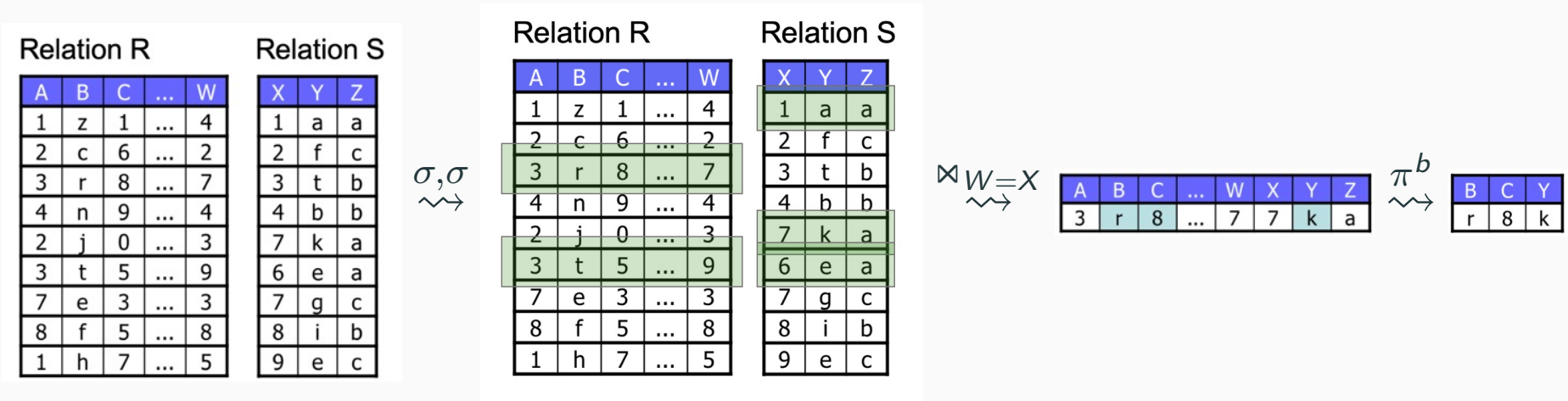
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Looks better

Candidate 2: Pushing selection down

Initial plan $\pi^b_{B,C,Y}\ (\sigma_{W=X\ \&\ A=3\ \&\ Z='a'}(R \times S))$
transforms, by pushing selection and theta-join definition laws, to
another plan $\pi^b_{B,C,Y}\ (\sigma_{A=3}(R)\ \bowtie_{W=X}\ \sigma_{Z='a'}(S))$



Looks better, especially, if we use indexes on A in R and on Z in S

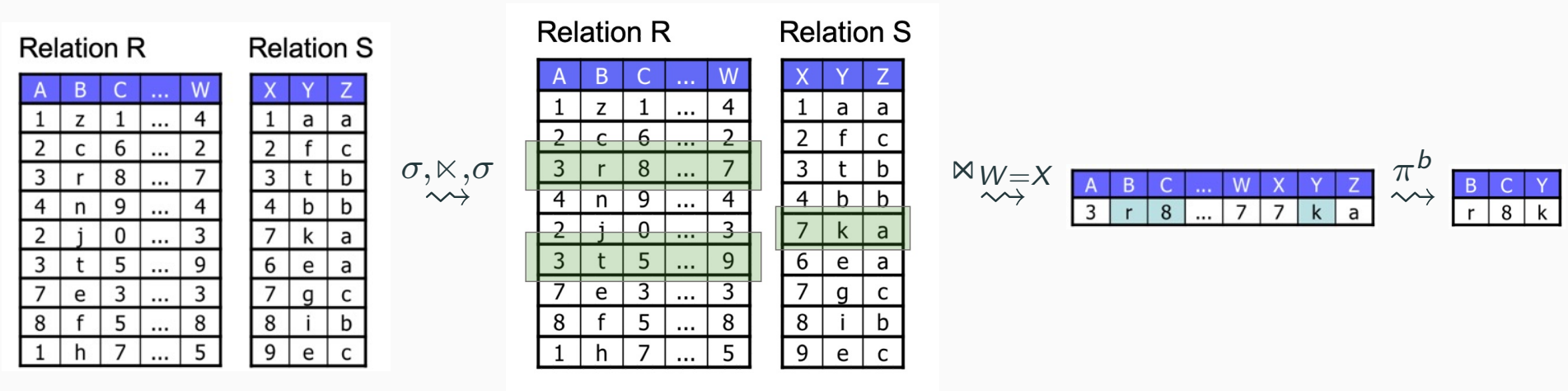
Candidate 3: More fine-grained

Candidate 1 (initial): $\pi^b_{B,C,Y}\ (\sigma_{W=X\ \&\ A=3\ \&\ Z='a'}(R \times S))$

Candidate 2: $\pi^b_{B,C,Y}\ ((\sigma_{A=3}(R)\ \bowtie_{W=X}\ \sigma_{Z='a'}(S)))$

Candidate 3: $\pi^b_{B,C,Y}\ ((\sigma_{A=3}(R)\ \bowtie_{W=X}\ \sigma_{Z='a'}(S \ltimes_{W=X} \sigma_{A=3}(R))))$

(here, $\ltimes_{W=X}$ is 'equi-semi-join', naturally expressible via ρ and $\ltimes$)



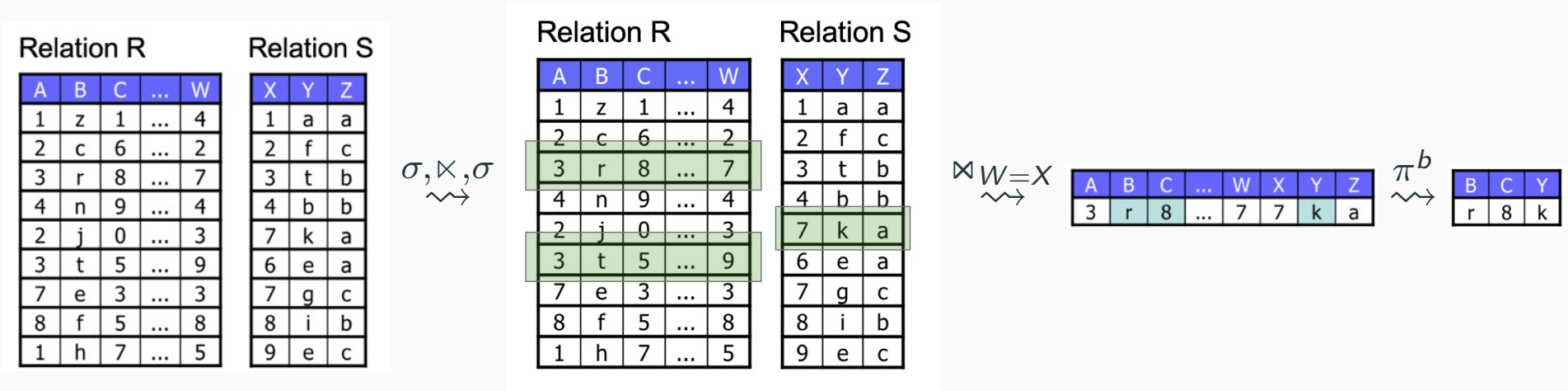
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More operations, but quicker

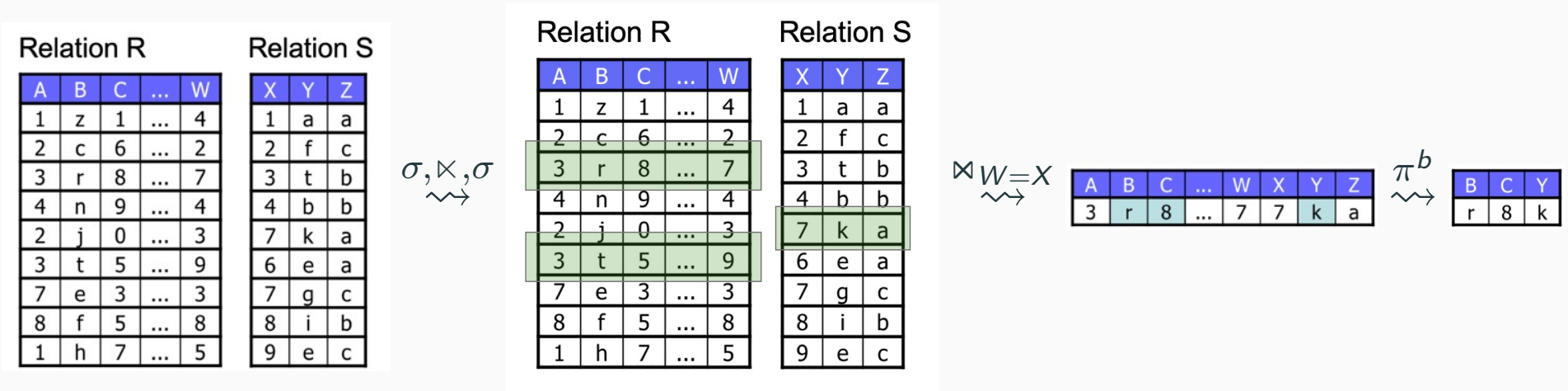
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(here, $\ltimes_{W=X}$ is 'equi-semi-join', naturally expressible via ρ and $\ltimes$)



More operations, but quicker,

especially, if we use indexes on A in R and X (not Z!) in S

4. Optimisation: Cost function

Cost function requirements

Recall: We need cost function f such that

f(Expr') $<$ f(Expr) in most cases means that

plan Expr' is quicker to evaluate than plan Expr

Evaluation time is spent for

- reading and writing to the secondary memory (e.g., disk I/O)
- evaluating RA operations in the main memory

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Real DBMS (advanced) cost functions take into account:

- (potentially different) evaluation time for operations (using algorithms discussed in the next lecture)
- indexes that decrease the number of reads (we know)
- reusing intermediate results (e.g., as in Candidate 3 above)
- pipelining intermediate results (tuples) from one operation to another without writing back to the disk

Our cost function

We take as our cost function:
the sum of estimates of sizes (in bytes) of the intermediate results (i.e., subexpressions) of the plan (i.e., the RA expression)

- estimate, because exact may be difficult to compute
  (our estimate is computed as described below)
- intermediate, because the inputs and the outputs are the same
- reflects the most important thing above: the number of disk I/O (number of used blocks is roughly proportional to the size of a relation)
- compositional: knowing estimates for immediate sub-plans, we can quickly compute the estimate for the plan (e.g., if we know the size estimates of Expr_1 and Expr_2, we can estimate the size of $\mathrm{Expr}_1 \bowtie \mathrm{Expr}_2$)
- quick to compute

Essentially, we assume that each operation is executed in negligible time and in isolation, and all the time is spent in reading all arguments (in whole) of each operation from the disk and writing the result back

Before we go: Example

Numbers are estimates(!) of subquery sizes

(e.g., neither 16000 nor 20000 may be the real size of the overall answer, and not counted anyway)



Our cost of the left plan: 2000+400+32000 = 34400

Our cost of the right plan: 2000+400+16000000+40000 = 16042400

Before we go: Example

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(e.g., neither 16000 nor 20000 may be the real size of the overall answer, and not counted anyway)



Our cost of the left plan: 2000+400+32000 = 34400

Our cost of the right plan: 2000+400+16000000+40000 = 16042400

Reflects our intuition: good cost function (at least for this case)

Notation

Thus, our main metric, for a (base or subquery) relation R:

$Size(R)$ – (estimation of) the size of R in bytes

(i.e., the main component of our cost, which is the sum of sizes)

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Thus, our main metric, for a (base or subquery) relation R:

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(i.e., the main component of our cost, which is the sum of sizes)

To estimate $Size(R)$ by induction by the query structure,
we will also maintain secondary metrics:

$Tups(R)$ – (estimation of) the number of tuples in relation R

$TupSize(R)$ – the (average) size of a tuple in R

as a result, we have $Size(R) = Tups(R) * TupSize(R)$

$Vals(R.A)$ – (estimation of) the number of different values of attribute A in R

real DBMSs use histograms instead (we will discuss them later)

Metrics for the base case: Statistics of physical relations

To compute costs for complex plans by induction, we need to start with statistics—that is, $Size(R)$, $Tups(R)$, $TupSize(R)$, $Vals(R.A)$, etc., for the base database relations R

Computing statistics may be expensive, and doing it after each update may be prohibitively costly

However, we do not need the exact values every time we estimate the cost of a plan, some inaccuracies is not a problem

System can recompute statistics only time to time
(automatically or manually)

Metrics for inductive case: Bag projection

Assuming uniform size of tuples (i.e., no VARCHAR, etc.),
the size and almost all secondary metrics for bag (generalised) projection $\pi^b_L(R)$ can be calculated accurately from metrics for R,
(due to bag semantics, one result tuple for each argument tuple):

- $\mathit{Tups}(\pi^b_L(R)) = \mathit{Tups}(R)$
- $\mathit{TupSize}(\pi^b_L(R))$ is defined by L
- $\mathit{Size}(\pi^b_L(R)) = \mathit{Tups}(\pi^b_L(R)) * \mathit{TupSize}(\pi^b_L(R))$

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- $Size(\pi^b_L(R)) = Tups(\pi^b_L(R)) * TupSize(\pi^b_L(R))$
- $Vals((\pi^b_L(R)).A) = Vals(R.A)$ if A is an attribute in L
- $Vals((\pi^b_{Expr \to A,\ \ldots}(R)).A)$ depends on $Expr$; by default, can be estimated as $\max(Vals(R.A_1), \ldots, Vals(R.A_n))$ where $A_1, \ldots, A_n$ are all different attributes of R mentioned in $Expr$

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  $\max(Vals(R.A_1), \ldots, Vals(R.A_n))$ where $A_1, \ldots, A_n$ are all different attributes of R mentioned in $Expr$

(We will cover set projection with duplicate elimination)

Metrics for bag projection: Example

Relation R:

A	B	C	D
1	cat	1999	a
2	cat	2002	b
3	dog	2002	c
4	cat	1998	a
5	dog	2000	c

Statistics of R:

- $Tups(R) = 5$
- $TupSize(R) = 4 + 20 + 4 + 10 = 38$
  (INT(4) + CHAR(20) + INT(4) + CHAR(10))
- $Size(R) = 5 * 38 = 190$
- $Vals(R.A) = 5$, $Vals(R.B) = 2$,
  $Vals(R.C) = 4$, $Vals(R.D) = 3$

Metrics for bag projection: Example

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Statistics of R:

- $Tups(R) = 5$
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  (INT(4) + CHAR(20) + INT(4) + CHAR(10))
- $Size(R) = 5 * 38 = 190$
- $Vals(R.A) = 5$, $Vals(R.B) = 2$,
  $Vals(R.C) = 4$, $Vals(R.D) = 3$

$S = \pi^b_{A+10 \to Aplus,\, B,\, A+C \to AC}(R)$:

- $Tups(S) = 5$
- $TupSize(S) = 4 + 20 + 4 = 28$
- $Size(S) = 5 * 28 = 140$
- $Vals(S.Aplus) = 5$, $Vals(S.B) = 2$ (both exact),
  $Vals(S.AC) = 5$ (estimation, 4 in reality)

Metrics for inductive case: Selection (overview)

The size of selection $\sigma_{Cond}(R)$ is much more difficult to estimate:

- $TupSize(\sigma_{Cond}(R)) = TupSize(R)$ (easy)
- so, $Size(\sigma_{Cond}(R)) = Tups(\sigma_{Cond}(R)) * TupSize(\sigma_{Cond}(R))$ relies on estimation of $Tups(\sigma_{Cond}(R))$
- we consider different types of $Cond$ separately
- by default, we naively assume uniform and independent distribution of $Vals(R.A)$ across relevant $R.A$
- real DMBSs use histograms for much better estimations
- estimation of all $Vals((\sigma_{Cond}(R)).A)$ with A mentioned in $Cond$ can be done similarly to $Tups$ (try it by yourself); for other attributes A we can take $Vals((\sigma_{Cond}(R)).A) = Vals(R.A) * Tups(\sigma_{Cond}(R))/Tups(R)$

Metrics for inductive case: Selection (atomic comparisons)

Estimating $Tups(\sigma_{Cond}(R))$ for atomic $Cond$:

- equality to a constant:
  $Tups(\sigma_{A=c}(R)) = Tups(R)/Vals(R.A)$ (may be not integer!)
- inequality to a constant:
  $Tups(\sigma_{A\neq c}(R)) = Tups(R) * (1 - 1/Vals(R.A))$ (or just $Tups(R)$)
- comparison to a constant:
  $Tups(\sigma_{A<c}(R)) =$

Metrics for inductive case: Selection (atomic comparisons)

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- inequality to a constant:
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- comparison to a constant:
  $Tups(\sigma_{A<c}(R)) = Tups(R)/3$ (or just $Tups(R)/2$)

- equality of attributes:
  $Tups(\sigma_{A=B}(R)) = (Tups(R)/\max(Vals(R.A), Vals(R.B))$
- inequality of attributes:
  $Tups(\sigma_{A\neq B}(R)) = Tups(R) * (1 - 1/\max(Vals(R.A), Vals(R.B))$ (or . . .)
- comparison of attributes:
  $Tups(\sigma_{A<B}(R)) = Tups(R)/3$ (or just $Tups(R)/2$)

Metrics for inductive case: Selection (atomic comparisons)

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- inequality of attributes:
  $Tups(\sigma_{A\neq B}(R)) = Tups(R) * (1 - 1/\max(Vals(R.A), Vals(R.B))$ (or . . .)
- comparison of attributes:
  $Tups(\sigma_{A<B}(R)) = Tups(R)/3$ (or just $Tups(R)/2$)

- comparisons with functions:
  $Tups(\sigma_{f(A_1,\ldots,A_n)\ \mathrm{op}\ g(B_1,\ldots,B_n)}(R)) = \ldots$

Metrics for atomic selection: Examples

Relation R:

A	B	C	D
1	cat	1999	a
2	cat	2002	b
3	dog	2002	c
4	cat	1998	a
5	dog	2000	c

Statistics of R:

- $Tups(R) = 5$
- $TupSize(R) = \ldots$
- $Size(R) = \ldots$
- $Vals(R.A) = 5$, $Vals(R.B) = 2$, $Vals(R.C) = 4$, $Vals(R.D) = 3$

Estimates of the number of tuples:

- $Tups(\sigma_{A=4}(R)) = 5/5 = 1$ (real: 1),
  $Tups(\sigma_{A\neq 4}(R)) = 5 * (1 - 1/5) = 4$ (4),
  $Tups(\sigma_{A<4}(R)) = 5/3 = 1.66$ (3)
- $Tups(\sigma_{B=\text{'cat'}}(R)) = 5/2 = 2.5$ (3),
  $Tups(\sigma_{B\neq\text{'cat'}}(R)) = 5 * (1 - 1/2) = 2.5$ (2)
- $Tups(\sigma_{A=C}(R)) = 5/5 = 1$ (0),
  $Tups(\sigma_{A\neq C}(R)) = 5 * (1 - 1/5) = 4$ (5),
  $Tups(\sigma_{A<C}(R)) = 5/3 = 1.66$ (5)

Metrics for inductive case: Selection (Boolean combinations)

Estimating $Tups(\sigma_{Cond}(R))$ for Boolean combinations of conditions:

- AND: $Tups(\sigma_{Cond_1 \& Cond_2}(R)) = Tups(\sigma_{Cond_1}(\sigma_{Cond_2}(R))) = Tups(\sigma_{Cond_2}(\sigma_{Cond_1}(R))) = Tups(R) * factor_{Cond_1} * factor_{Cond_2}$
  (assumes independence)

- NOT: $Tups(\sigma_{\neg Cond'}(R)) = Tups(R) - Tups(\sigma_{Cond'}(R))$

- OR: $Tups(\sigma_{Cond_1 \vee Cond_2))}(R)) = Tups(\sigma_{\neg(\neg Cond_1 \& \neg Cond_2))}(R)) = Tups(R) * (1 - (1 - factor_{Cond_1}) * (1 - factor_{Cond_2}))$
  (assumes independence)

Metrics for selections with Boolean combinations: Examples

Relation R:

A	B	C	D
1	cat	1999	a
2	cat	2002	b
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4	cat	1998	a
5	dog	2000	c

Statistics of R:

- $Tups(R) = 5$
- $TupSize(R) = \ldots$
- $Size(R) = \ldots$
- $Vals(R.A) = 5$, $Vals(R.B) = 2$, $Vals(R.C) = 4$, $Vals(R.D) = 3$

Estimates of the number of tuples:

- $Tups(\sigma_{A=4\ \&\ B=\text{'cat'}}(R)) = 5 * 1/5 * 1/2 = 0.5$ (real: 1),
  $Tups(\sigma_{A\neq 4\ \&\ B\neq\text{'cat'}}(R)) = 5 * 4/5 * 1/2 = 2$ (2)
- $Tups(\sigma_{A=4\ \vee\ B=\text{'cat'}}(R)) = 5 * (1 - (1 - 1/5) * (1 - 1/2)) = 3$ (3),
  $Tups(\sigma_{A\neq 4\ \vee\ B\neq\text{'cat'}}(R)) = 5 * (1 - (1 - 4/5) * (1 - 1/2)) = 4.5$ (4)

Metrics for inductive case: Natural join (overview)

The size of natural join $R \bowtie S$ (and other joins) is also difficult:

- $TupSize(R \bowtie S)$ is the sum of sizes of distinct attributes in R and S
- so, $Size(R \bowtie S) = Tups(R \bowtie S) * TupSize(R \bowtie S)$ relies on estimation of $Tups(R \bowtie S)$
- to estimate $Tups(R \bowtie S)$ and $Vals((R \bowtie S).A)$ for join attributes A we rely on value containment assumption:
  If A is an attribute in R and S such that $Vals(R.A) \leq Vals(S.A)$ then every value of A in R appears in A of S (cf. foreign key)

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- to estimate $Vals((R \bowtie S).A)$ for non-join attributes A we rely on value preservation assumption:
  If A is in R but not in S then $Vals((R \bowtie S).A) = Vals(R.A)$ (and symmetric for A in S but not in R)

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- to estimate $Vals((R \bowtie S).A)$ for non-join attributes A we rely on value preservation assumption:
  If A is in R but not in S then $Vals((R \bowtie S).A) = Vals(R.A)$ (and symmetric for A in S but not in R)
- real DMBSs use histograms for much better estimations
- other joins are expressible, and we can use the defining laws for estimation

Metrics for inductive case: Natural join (one join attribute)

Estimating $R \bowtie S$ with one join (i.e., common) attribute A (using these two assumptions):

- if $Vals(R.A) \leq Vals(S.A)$ then each tuple in R will match approximately $Tups(S)/Vals(S.A)$ tuples in S
- thus, in general, $Tups(R \bowtie S) = Tups(R) * Tups(S)/\max(Vals(R.A), Vals(S.A))$
- $Vals((R \bowtie S).A) = \min(Vals(R.A), Vals(S.A))$
- $Vals((R \bowtie S).A') = Vals(R.A')$ for each non-join A' in R
- $Vals((R \bowtie S).A') = Vals(S.A')$ for each non-join A' in S

Metrics for natural join: Example 1

Relations R and S:

Relation R

A	B	C	...	X
1	z	1	...	4
2	c	6	...	2
3	r	8	...	7
4	n	9	...	4
2	j	0	...	3
3	t	5	...	9
7	e	3	...	3
8	f	5	...	8
1	h	7	...	5

Relation S

X	Y	Z
1	a	a
2	f	c
3	t	b
4	b	b
5	k	a
6	e	a
7	g	c
8	i	b
9	e	c

Statistics of R and S:

- $Tups(R) = 9$, $Tups(S) = 9$
- $TupSize(R) = \ldots$, $TupSize(S) = \ldots$
- $Size(R) = \ldots$, $Size(S) = \ldots$
- $Vals(R.A) = 6$, $Vals(R.X) = 7$, $Vals(S.X) = 9$, $Vals(S.Z) = 3$

Estimates (all correct, since essentially primary & foreign keys):

- $Tups(R \bowtie S) = Tups(R) * Tups(S) / \max(Vals(R.X), Vals(S.X)) = 9$ (real: 9)
- $Vals((R \bowtie S).X) = \min(Vals(R.X), Vals(S.X)) = 7$ (7)
- $Vals((R \bowtie S).A) = Vals(R.A) = 6$ (6)
- $Vals((R \bowtie S).Z) = Vals(S.Z) = 3$ (3) (these may be different even with the keys)

Metrics for natural join: Example 2

Relations R and S:

Relation R

A	B	C	...	X
1	z	1	...	4
2	c	6	...	2
3	r	8	...	7
4	n	9	...	4
2	j	0	...	3
3	t	5	...	9
7	e	3	...	3
8	f	5	...	8
1	h	7	...	0

Relation S

X	Y	Z
1	a	a
2	f	c
3	t	b
4	b	b
5	k	a
6	e	a
7	g	c
8	i	b
9	e	c

Statistics of R and S:

- $Tups(R) = 9$, $Tups(S) = 9$
- $TupSize(R) = \ldots$, $TupSize(S) = \ldots$
- $Size(R) = \ldots$, $Size(S) = \ldots$
- $Vals(R.A) = 6$, $Vals(R.X) = 7$, $Vals(S.X) = 9$, $Vals(S.Z) = 3$

Estimates (no foreign key any more):

- $Tups(R \bowtie S) = Tups(R) * Tups(S) / \max(Vals(R.X), Vals(S.X)) = 9$ (real: 8)
- $Vals((R \bowtie S).X) = \min(Vals(R.X), Vals(S.X)) = 7$ (6)
- $Vals((R \bowtie S).A) = Vals(R.A) = 6$ (6)
- $Vals((R \bowtie S).Z) = Vals(S.Z) = 3$ (3)

Metrics for inductive case: Natural join (many join attributes)

Estimating $R \bowtie S$ with several join attributes $A_1, \ldots, A_n$ (using these two assumptions):

- applying the same logic, we have $Tups(R \bowtie S) =$

$$\frac{Tups(R) * Tups(S)}{\max(Vals(R.A_1), Vals(S.A_1)) * \ldots * \max(Vals(R.A_n), Vals(S.A_n))}$$

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- for $n = 0$ we have Cartesian product:

$$Tups(R \bowtie S) = Tups(R) * Tups(S)$$

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$$\frac{Tups(R) * Tups(S)}{\max(Vals(R.A_1), Vals(S.A_1)) * \ldots * \max(Vals(R.A_n), Vals(S.A_n))}$$

- for $n = 0$ we have Cartesian product:
  $Tups(R \bowtie S) = Tups(R) * Tups(S)$

- $Vals((R \bowtie S).A)$ is as before:
  $\min(Vals(R.A_i), Vals(S.A_i))$ for each join A_i,
  $Vals((R \bowtie S).A') = Vals(R.A')$ for non-join A' (in R)

Metrics for inductive case: bag-theoretic operations

Estimating metrics for bag union, intersection and difference:

- $\mathit{TupSize}(R \cup^b S)$, $\mathit{TupSize}(R \cap S)$, $\mathit{TupSize}(R \backslash S)$ are inherited from the arguments
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- set-theoretic union can be estimated via duplicate elimination (see below)

Metrics for inductive case: duplicate elimination and grouping

Estimating metrics for duplicate elimination:

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Estimating metrics for grouping with aggregation:

- similar to duplicate elimination (write it down by yourself)
- the only new case is $Vals((\gamma_{Agg(A)\to A'}(R)).A'))$: we can take $Tups(\gamma_{Agg(A)\to A'}(R))/2$ (i.e., every aggregate value appears twice on average)

Histograms

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Real DBMSs uses more fine-grained histograms:

- simple histogram: number of tuples in R for each value of A
- advanced (when $Vals(R.A)$ is large): number of tuples in R for intervals of values of A (many techniques to pick the intervals)
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Often, a hybrid approach is used: histograms in the statistics, $Vals(R.A)$ with uniform distribution assumption for sub-plans

Plan costs: Come back to the example

Relation R

A	B	C	...	W
1	z	1	...	4
2	c	6	...	2
3	r	8	...	7
4	n	9	...	4
2	j	0	...	3
3	t	5	...	9
7	e	3	...	3
8	f	5	...	8
1	h	7	...	5

Relation S

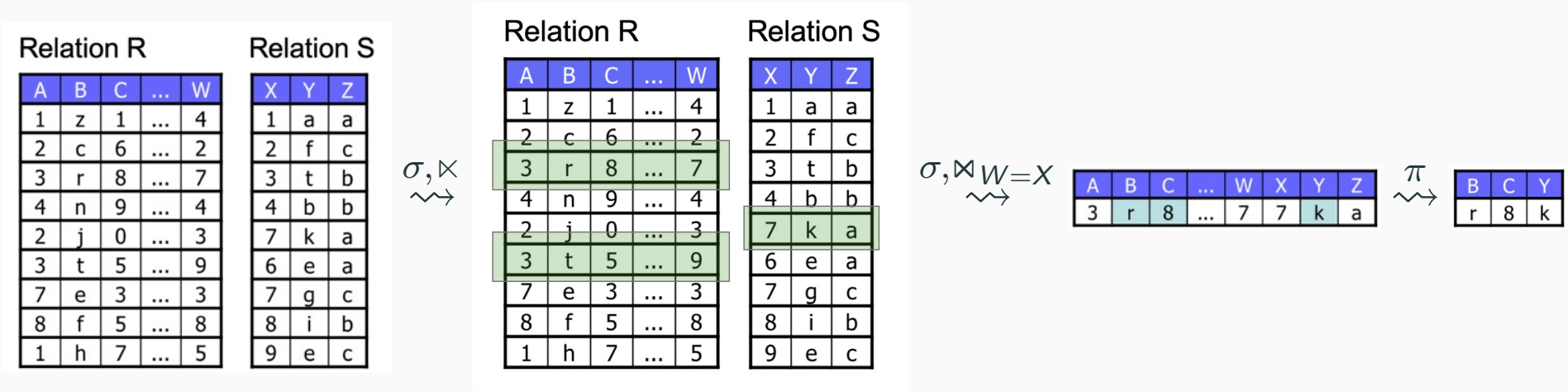
X	Y	Z
1	a	a
2	f	c
3	t	b
4	b	b
7	k	a
6	e	a
7	g	c
8	i	b
9	e	c

Plan 1 (initial): $\pi_{B,C,Y}\ (\sigma_{W=X\ \&\ A=3\ \&\ Z='a'}(R \times S))$

Plan 2: $\pi_{B,C,Y}\ ((\sigma_{A=3}(R)\ \bowtie_{W=X}\ \sigma_{Z='a'}(S)))$

Cost of Plan 2 ($Size(\sigma_{A=3}(R)) + Size(\sigma_{Z='a'}(S)) + Size(\ldots \bowtie_{W=X} \ldots)$) is clearly better than cost of Plan 1 ($Size(R \times S) + Size(\sigma_{\ldots}(R \times S))$)

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Plan 3: $\pi_{B,C,Y}\ ((\sigma_{A=3}(R)\ \bowtie_{W=X}\ \sigma_{Z='a'}(S \ltimes_{W=X} \sigma_{A=3}(R))))$

(here, $\ltimes_{W=X}$ is 'equi-semi-join', naturally expressible via ρ and $\ltimes$)

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Homework: compute and compare the costs of Plans 2 and 3

5. Optimisation: Heuristics

Searching for a plan with good cost

As we discussed, given an initial query plan (RA expression) Expr, we have a huge search space of plans to compare with

DBMSs pragmatically find another query plan Expr' such that

- Expr and Expr' are equivalent (i.e., give the same answer on all possible data instances)
- Expr' is estimated to be quicker than other candidates using the cost function (for us: sum of sizes of intermediate sub-queries in the plan)

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They use greedy heuristic:

- starting from the initial Expr, they apply the algebraic laws one by one, trying to decrease the cost on (almost) each step as much as possible
- stops with a selected plan when there are no more cost improvements

Common rules

The algebraic laws that (almost always) decrease our cost:

- Push selections as far down as possible
- If the selection condition consists of several parts (AND or OR), split into multiple selections and push each one as far down the tree as possible
- Push projections as far down as possible
- Combine selections and joins (especially, Cartesian products) to appropriate theta-joins
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Real DBMS cost functions are more fine-grained, and these rules may be less universal (e.g., due to indexes)

Order of joins

One of the most important practical question for optimisation is the order to join—that is, how to evaluate

$$(\ldots(R_1 \bowtie R_2) \bowtie \ldots \bowtie R_{n-1}) \bowtie R_n$$

Good estimates of intermediate results here are crucial for efficient evaluation (and the difference may be huge)

In general, the search space (all possible orders of $(\ )$) is large

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Even the choice between $R_1 \bowtie R_2$ and $R_2 \bowtie R_1$ is not trivial: the join algorithms are not symmetric (but our cost function does not distinguish these cases)

What we learned?

How DBMSs compile queries to RA plans and optimise to presumably better plans

Next time: how plans are evaluated